REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
17/Jan/2002

2. REPORT TYPE
MAJOR REPORT

3. DATES COVERED *(From - To)*

4. TITLE AND SUBTITLE
UTILIZING PATTERNS IN US MILITARY INTERVENTIONS TO IMPROVE LOGISTICS DECISION MAKING

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
CAPT BELL JOHN E

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
AUBURN UNIVERSITY MAIN CAMPUS

8. PERFORMING ORGANIZATION REPORT NUMBER
CI02-3

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
THE DEPARTMENT OF THE AIR FORCE
AFIT/CIA, BLDG 125
2950 P STREET
WPAFB OH 45433

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Unlimited distribution
In Accordance With AFI 35-205/AFIT Sup 1

DISTRIBUTION STATEMENT A:
Approved for Public Release -
Distribution Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

20020204 090

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE		26	19b. TELEPHONE NUMBER *(Include area code)*

UTILIZING PATTERNS IN US MILITARY INTERVENTIONS TO IMPROVE LOGISTICS DECISION MAKING

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ABSTRACT

The field of political science has had difficulty predicting where the next conflict will occur using strictly quantitative methods. However once a conflict does occur, there seems to be some logical variables such as oil or level of democracy that contribute to the US's willingness to commit military forces abroad. How these variables relate and interact in determining the US decision of whether or not to enter a conflict is a difficult matter. No known traditional linear model to predict US conflict decisions has been formulated. This research proposes a list of variables that might impact intervention decisions and puts forth a neural network approach to analyzing the underlying interactions present in existing conflict data. This method explores the interactive and possibly non-linear nature of conflict decision making. The results indicate that a reasonably small number of variables can be used to predict when the US might enter a conflict. Finally, the results of this analysis are then applied to a logistics location problem in order to show how eliminating some degree of uncertainty might significantly improve inventory positioning decisions.

INTRODUCTION

A great deal of time and effort is spent in the business world predicting the future demand and subsequent sale of products in the marketplace. Demand forecasting is used by companies to determine the production requirements and inventory needs for individual products in the upcoming months and years. A company's goal to maximize its profits or its shareholder's wealth and the highly competitive nature of the global marketplace make the importance and rigor of demand forecasting an important element for success in the market. However, in non-profit, military and other government sectors demand forecasting for highly variable, non-competitive, and emergency demand items cannot be

accomplished with the same logic and practices used by the business community to determine the demand for a constant flow of goods desired by their customers. For organizations such as the US military, the Federal Emergency Management Agency (FEMA), the American Red Cross (ARC), etc., the ability to respond quickly to austere locations with the right amount of material, equipment and personnel can literally be a matter of life or death for the members of the organization or its customers. However, predicting demand for these organizations cannot be accomplished with straightforward market surveys or analyses of the past demand for a similar product. For emergency response agencies, the demand and subsequent positioning of resources or personnel depends on dynamic variables such as drought, natural disasters and civil unrest in different parts of the world. Similarly, for the US military, demand forecasting literally follows from predictions about the stability of the world and where forces are most likely to be engaged in conflicts. Unfortunately, the warning or lead time to respond to these crises is not always sufficient to transport the needed material or personnel to the location in order to meet military objectives or save lives. With this in mind, certain amounts of pre-positioned military equipment and material are stored around the world to meet the demands of an impending conflict or crises. Where to best position this inventory to maximize the ability of the military to respond to a demand is inexorably tied to the political forecasts and intelligence reports about the changing state of the world. Naturally, in our most cynical gaze at the world of political science it might appear that there are a handful of overarching variables that induce the US as a world power to engage in a conflict with another political state or to intervene in a conflict between two or more states. For example, variables such as religion, trade, or oil seem to play an

important role in the decision making of US politicians as they determine when and where to use US military force. Of course, many other equally important variables can be considered part of our vital national interest and at times play important roles in determining the use of military force by the US. The difficulty of understanding how political variables relate and interact makes quantitative analysis and prediction of future events a seemingly impossible task. However, forecasting has never proven to be a perfect science but instead aims to make continuous improvements on understanding future demands. With these limitations in mind, it is the goal of this article to begin to identify those variables that might influence the US to enter into a conflict abroad and then quantitatively explore patterns in past US action as a possible factor for determining future US military intervention strategy. It is believed that the ability to more closely predict possible US military action will serve as a surrogate for demand forecasting for those who need to make inventory positioning decisions prior to the outbreak of a conflict. In the end, any improvement in the decision making for pre-positioned military equipment will hopefully reduce costs and deployment times and save the lives of those involved in a military conflict once it has begun.

LITERATURE REVIEW

A comprehensive quantitative analysis of the historical use of US military forces from 1946-1975 (Blechman & Kaplan, 1978) attempted to determine the results of US military action abroad in order to determine if military intervention should be used by decision makers to achieve political objectives and if so under what conditions. At the conclusion of this study, the authors pointed out that in deciding on the structure of US forces and their operational and deployment patterns, one should consider possible future

political uses of the military. They point out that if US military forces are acquired and operated solely to meet the needs of the "worst case" or big wars, then they will not be prepared for many more likely cases where military force will be used. Historically, the US has prepared to fight the next world war or major regional conflict. The positioning of forces and inventory to support these forces is primarily the result of the cold-war and takes into account the large expected conflicts that might have occurred in Western Europe and the Korean Peninsula. In addition, (Millett, 2000) suggests that the military should do some modest restructuring that would prepare them for limited contingency operations and interventions and that the military may have already passed the line where they can do more and more with less. If this is true, then repositioning the remaining scarce resources of the military should be a priority and one that takes into consideration not only improbable major threats to national security, but also more probable use of military forces in smaller limited interventions and contingencies abroad. This sentiment is echoed by (Nye, 1999), who states that even though we should position our forces abroad to protect our "A-list" priorities, we still will not be able to ignore B and C-list problems and demands for military forces they require.

Variables that Influence US Intervention

In their initial classification, Blechman and Kaplan identified and examined five contextual features related to US conflicts abroad: region, time period, Russian/Chinese involvement, political situation, and the participation of other states. Additionally, they found four correlates of success in their research: the nature of the US objectives, the context of the incident, the level of Soviet involvement and the nature and type of

military forces involved. Also, Blechman and Kaplan found that the use of military force seemed most favorable in the short run and faded as time went on

A detailed quantitative analysis of the effects of alliances was also conducted by (Tillema, 1989). This research used a broad definition of the term intervention which includes all instances where the US enters an ongoing conflict between two countries and anytime the US independently initiates a conflict with a foreign state. The study found that alliances did increase the likelihood of defensive-natured interventions and decreased the likelihood of offensive natured interventions in an allied country. These study did imply under what conditions the US might intervene in a country with which it has an alliance, but did not analyze the conditions and connections of other variables that might cause the US to intervene abroad.

Although not a primary focus of the research, other studies have similarly identified important variables that influence decision making related to the application of military forces in foreign lands. In a more recent quantitative study, (Meernik, 1996) states national security and the promotion of democracy have been used with "regularity and frequency" by US presidents to explain and defend the use of force in foreign conflicts. Other studies also concentrate on the use of force by the US to promote democracy (Von Hippel, 2000), (Peceny, 1999). However, these studies acknowledge that the promotion of democracy or any set of variables cannot be said to be the sole goal of all US interventions. Although less direct research has been conducted, other studies on conflict do identify additional variables besides the promotion of democracy that influence the decision to use military force in foreign conflicts. For example, (Kanter & Brooks, 1994) and (Meernik, 1996) point out that variables such as the region of the

conflict, the success/failure of previous interventions, commitment of allies, or the GDP per capita of the countries involved may at times be influential variables in determining US action, . In addition, (Von Hippel, 2000) suggests that other variables such as the presence of refugees, the media exposure, success of sanctions, defiance of foreign rulers, and the relative power and size of the country may also be important variables. Other possible variables are dependent on the current US President who ultimately makes the final decision on when and how to use military forces abroad. The President's own military background, political party, election pressures, and the foreign issues that gain his attention may all influence how and where US military force may be used by a particular president according to research by (Deconde, 2000) and (Peceny, 1999). In addition to these examples, dozens of additional variables affecting the decision to use US military force abroad can by hypothesized. However, in reviewing the literature, no comprehensive list of possible variables influencing US action appears to have been gathered. In building such a list, it is important to recognize as previously stated that a purely exhaustive list may not be able to be accumulated and that the variables that relate to certain conflicts appear to change dramatically from case to case. Review of several additional sources including (Byman, 1998), (Sangvic, 1999),(Blechman, 1985), (Johnson, 1997), (Luttwak, 1999), (LaMoe, 1999) and (Tillema, 1994) has resulted in an initial list of possible variables in Table I . This list has been divided into five categories including the political variables of the foreign states, socio-economic-military variables of the foreign states, US political variables, situational variables of the conflict, and Presidential variables.

Study of the potential variables identified in Table I, makes it clear that many of the variables are extremely difficult to operationalize and measure and others are not. In addition, some of the variables are static and do not change for a particular country or situation with a great degree of magnitude. For example, the region, religious makeup and even the GDP per capita for a particular country do not tend to change greatly from year to year. However, other variables such as the probability of success, migration of refugees, or the threat of terrorism might literally change overnight.

Table I: Variables influencing US intervention decisions

Class	Variable/Question
Political Variables of Foreign Countries	
	Levels of democracy of the primary states involved
	Terrorism activity and sponsorship by states involved
	Drug production/transshipment by states involved
	Do the states possess nuclear weapons or weapons of mass destruction
	Are the states part of alliance such as NATO
	Are the states influential members of the UN
	Does the US have friendly diplomatic relations with states involved
	Is Security assistance and arms being supplied by US to the states
Socio-Economic-Military Variables of Foreign Countries	
	Region of states involved
	Population of the states involved
	Primary Race and Religions of the states
	Industrial/technical development of the states involved
	What is the size/GDP of the economies of the states
	How wealthy are the nations in terms of per capital GDP
	Are the states major US trade partners
	Do the states possess major oil reserves or other strategic resources
	Does the region possess a major transportation infrastructure
	What is the size and capability of the foreign military's involved
US Political Factors	
	Do the American People support goals of intervention
	What is the probability of success for a US intervention
	To what extent will the US military take casualties
	How has the US media portrayed the conflict
	Does the US have a commitment to an ally in the conflict
	Is the environment threatened
	Are mass migrations or humanitarian needed shaping US opinion
	Can the US maintain security/commitments in rest of world
	Is the UN sactioning US intervention

Table I. (Continued)

Class	Variable/Question
Presidential Variables	
	Military Experience of the current President of the US
	Foreign Diplomatic Experience of the President
	Political Party of the President
	Does the conflict have the attention of the President
Situational Variables of the Conflict	
	Is the security of the US threatened
	Are Civil rights or genocide factors in the conflict
	What is the commitment of foreign populations to the conflict
	Is there an insurgency or invasion to counter
	Is it an intrastate problem such as a civil war, failed state or civil strife
	Is humanitarian aid and/or large number of refugees involved
	Is there another great state such as Russia or China involved
	Will a US military intervention be offensive or defensive in nature
	Are we retaliating for a attack on US territory/people/resources
	What has been the success or failure of most recent US interventions
	What is the possible time-frame and level of risk of the intervention
	Is a domestic assailant being pursued into a foreign state
	Period in history – Post Vietnam, Pre or Post Cold War, etc.

Therefore, it is important to recognize that a model or framework that uses any of these dynamic variables for prediction of future US involvement must be continuously updated as the variables change. Added to this problem it can be seen that there exists as a minimum dozens of potential variables for any model. The use of typical methods of quantitative analysis such as polynomial regression might make it necessary to explore a great number of terms especially when higher order and interaction terms are considered in any model. In addition, such a technique might not explore the possible non-linear relationship of possible variables. One technique that has recently been applied to political science research to identify patterns within a large amount of data is the use of neural networks to understand the probability of a conflict occurring between two states (Beck, 2000). This research effort will use similar techniques to try to identify patterns in

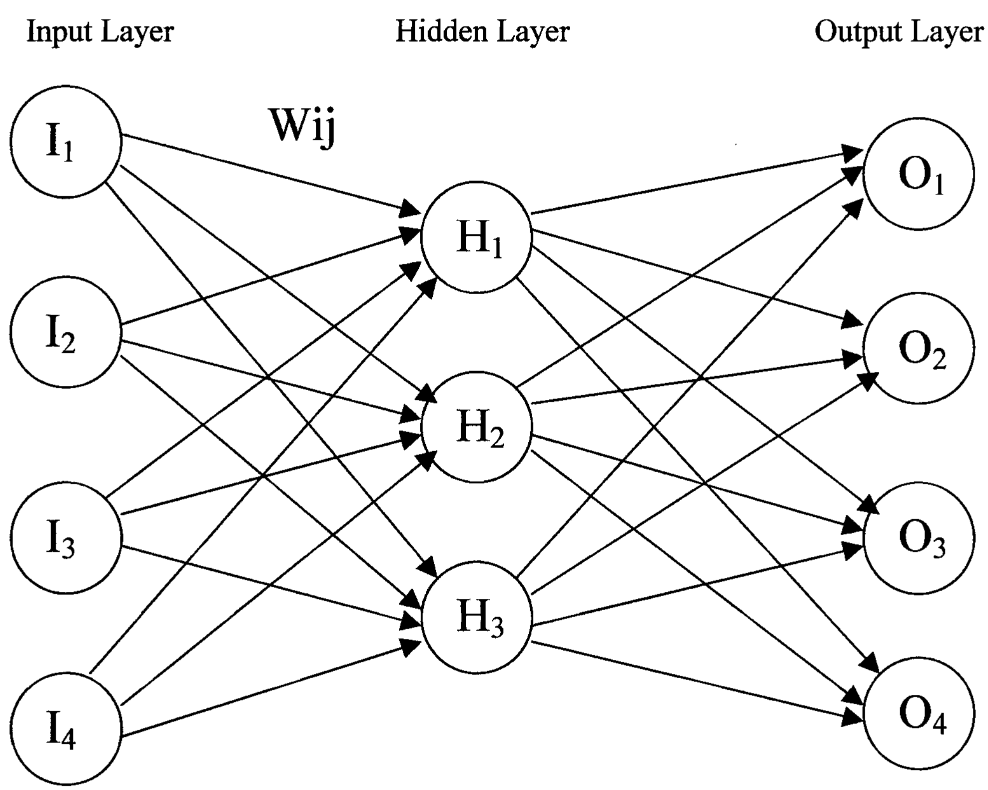
US military use abroad using a limited number of variables. Although, the ability to measure all of the variables in Table I is currently not available, it is hoped that patterns in US interventions can be identified using several of the variables with available measures. Such success will not only lead to better decision-making for pre-positioned military inventory in the near future, but might justify the measurement and updating of data for additional variables that are thought to influence military use in foreign conflicts.

METHODOLOGY

The use of artificial neural networks has grown in popularity as a method for identifying patterns and making forecasts in complicated research settings. An informative overview of the development, function and different types of artificial neural networks is described by Jain and Mao (Jain, 1996). In addition, more detailed quantitative descriptions of the functioning of artificial neural networks are also available (Chauv and Rummel,) and (Hertz et al,). Artificial neural networks were inspired by research in the biological sciences and are based on the operation of biological neural networks in the inner workings of the brain. At its most basic level, the brain consists of individual neurons which are connected in a massively parallel system. Each neuron receives electrical impulses through branches called dendrites and similar outputs impulses to other neurons through branches called axons. Although, the basic units seem to perform a relatively simple process, the result is a highly flexible and adaptive system with the ability to learn, categorize, compute and generalize about inputs not previously encountered. Through the use of artificial neural networks, researchers attempt to obtain similar abilities and results in their own decision making processes.

Neural networks can be essentially divided into two categories, feed-forward or recurrent networks. Several advanced neural network techniques including Hopfield Networks, Kohonen Self-Organizing Maps, and Competitive Networks include feedback loops in the neural structure and are therefore part of the recurrent category of neural networks. This research applies a more common feed-forward model where the flow of all actions and computations moves from the input layer of neurons to the output layer as seen in Figure 1

Figure 1: Feedforward neural network



The network is initially provided a set of training data as input and using a learning algorithm it conducts an iterative adjustment of the weights in the model to match known

outputs. Once the model is adequately able to predict known results, it is then tested against additional cases and used to make predictions.

A common learning algorithm for a feedforward network is called backpropagation which is used to adjust trial inputs to match known outputs in the model. The development of the backpropagation technique can be attributed to (Rummlehardt and McClellan,1986) and has been successfully applied in decision-making in fields other than political science by (Leonard et al,) (Reyes-Alduroso, et al, 1999). An informative description of the backpropagation algorithm is provided by (Knight, 1990).

Backpropagation is a multilayer technique that uses a hidden layer of units in order to capture complex features of the data through internal representations. All units in the feedforward network are fully connected to units in the next layer and each connection has a weight, W_{ij}, associated with it. The initial weights are usually randomly generated. In addition, a response function is used by the hidden layer and output layer to transform inputs into outputs in the model. Typically a sigmoidal function is used for this purpose. For example, the value for hidden unit H_1 in Figure 1 can be expressed as the value resulting from inputting the weighted sum of each input plus a bias value into the sigmoidal response function: 1/1+-exp((sum Wi1 I1j)+bias). The hidden unit values are then weighted by the next set of connection weights and input into the sigmoidal function again to provide values for the output units. These generated outputs are then compared to expected output values to determine an error value which is a measure of how close the model came to predicting a known output. This error value is then used to adjustment the weights and biases in the hidden layer of the network. Weight adjustment is typically done using an equation that multiplies the old weight by the amount of error,

the size of the previous input unit and a fixed learning rate value. After adjustments are made to weights from the hidden layer, error estimates are similarly propagated back through the network to the original input layer and weights and biases are adjusted accordingly. Unlike other algorithms, the error adjustment in backpropagation is made for each input-output pair in the original "training" set of data. Once each input-output pair has been seen by the model one time, an "epoch" is said to have been completed. It may take many epochs for a model to be sufficiently trained on a set of data. Finally, once the model has been trained it can be used to make output predictions when given new sets of inputs.

Of course there may be drawbacks to using a neural network approach for any research effort. First, a great deal of data for training will usually be necessary for the model to adequately learn the existing patterns. Also, researchers must protect against the model memorizing or over-fitting the original data. If the model simply "memorizes" the data in the original training set it will loose its ability to make robust predictions when new data is input into the final model. In addition, a simple feed-forward model may not adequately model the changing environment in time series data and it may be found that more advanced recurrent techniques are needed.

Research Questions and Data

The primary question in this study is whether a small group of measurable variables of the countries involved in a dispute as seen in Table I can be used as inputs to a feedforward neural network to accurately model US intervention patterns in historical data. To answer this question, a sequential approach is used to build three separate neural networks to predict intervention patterns. Model 1 contains two input variables:

Region and Religion. Model 2 contains these same variables and also includes Level of Democracy and the Drug Involvement of the countries in the dispute. Finally, model 3 contains these four variables and also includes the Oil resources and Per Capita GDP of the countries involved. The results of each model will be used to answer the hypotheses that model 2 performs better than model 1 and model 3 performs better than model 2.

Since conflicts, by definition, include two or more countries, the data input into the neural network must include the values for the input variables for at least two countries. This approach is consistent with the dyad approach used in previous political science research (Tucker, 1997), (Beck et al, 1997) and (Lemke and Reed, 2001). For this study, the inputs are limited to the two primary countries in the conflict and do not take into account the variable values of additional countries which join the dispute. This limitation is necessary to simplify the model and necessary quantitative computations.

A well-known and utilized database from the field of political science, the Militarized Interstate Dispute (MID) database, version 2.10 is used as the primary source of information on the occurrence of conflicts and disputes. This database contains data on political disputes from 1816-1992 and was compiled by the Correlates of War (COR) Project (Jones et al.). The MID database does indicate which countries are the originators of the dispute and how many countries are involved in each dispute. However, the MID database does not include most of the descriptive variables about countries involved in a dispute. Therefore, several other groups of data had to be added to the dispute data prior to input into the neural network models.

Data about the region, religion, per capita GDP and drug involvement of each country were obtained from the US Central Intelligence Agencies' Worldfactbook 2000

(CIA, 2000). The coding for these individual variables can be seen in the Appendix. Next, information on the level of democracy of individual countries at the time of a particular dispute was obtained from the Polity database originally developed by Jaggers & Gurr (Polity, 2000). This database gives a polity score ranging from -10 (complete autocracy) to 10 (maximum democracy) for the year the conflict occurred. Since the Polity III database does not use an identical set of countries as the MID database, there are a handful of small countries that do not possess polity scores and they are given a neutral score of zero in the instances where they appear in the data. The list of these countries can be seen in the Appendix. The quantity of oil resources possessed by individual countries around the world was obtained from the US Department of Energy's Energy Information Administration (World, 2001).

In order to limit the size of the data and to limit the number of confounding historical variables, the study data are limited to the years following the Vietnam War and start with the year 1974. The MID data set currently does not contain data past 1991, therefore, the data consist of 586 conflicts from 1974-1991. The data set has been divided into two groups by randomly assigning 80% of the conflicts into a training set of 480 conflicts and placing the remaining 106 conflicts in a test set. In this manner the data is trained on the larger set of data and then the accuracy of each model is tested by comparing the model's prediction with known results in the testing set. The operation of each of the three neural networks also used a constant set of values in order to compare the output results. First, each model was ran thirty times using a random set of weights as an initial starting point in order to insure the results were consistent and to ensure that the initial weights themselves were not interfering with the analysis. In addition, during

training each model was allowed to run for 2000 epochs in order to allow the model adequate time to try to reach the target values. The objective of the models was to minimize the difference in the model output probabilities verses known target values (0 for no conflict and 1 for a conflict) as measured by the root mean squared error. In addition, the success of the model was also judged by the number of conflicts it predicted correctly within a set tolerance level. For the training data set, the tolerance level was set at .25 for each output value. This value allowed each output within 25% of the target to be considered correct. The testing data set uses a tolerance limit of .50 value which is set at the midpoint to discriminate probability values into distinct yes or no answers of whether the US entered into a conflict or not.

RESULTS

The results of the three neural network models provide evidence that even a small number of variables can provide a fairly robust prediction of whether the US would enter into a conflict with a foreign state or intervene in an ongoing conflict between two other states. The results from the three models are listed in Table II and are separated into separate results for the training and testing data sets and include the average numerical and percentage results for the number conflicts measured correctly by the model. The average root mean squared error achieved by each model is listed as well as the tolerance and number of epochs. Initial inspection of the results reveal that model 1 is able to successfully measure 84% of the training conflicts and accurately predict 87% of the conflicts in the test set. These results are greatly improved upon in model 2 which achieves a 95% success rate in the training set and a 96% success rate in the test data set.

The differences between model 2 and model 3 are not as obvious and for both the test data set and the training data set it appears they achieve relatively similar results.

Table II: Neural Network Model Results

	Model 1		Model 2		Model 3	
Measure	Training	Testing	Training	Testing	Training	Testing
Conflicts	480	106	480	106	480	106
Ave. RMS Error	.2908	.3036	.1383	.1608	.1356	.1789
Mean Number Correct	401	92.7	455.2	102.1	456.4	101
Mean Number Incorrect	79	13.3	24.8	3.87	23.57	5.03
% Correct	84	87	95	96	95	95
% Incorrect	16	13	5	4	5	5
Training Epochs	2000	2000	2000	2000	2000	2000
Tolerence	.25	.5	.25	.5	.25	.5

Similarly, the average root mean squared error (RMS) for model 1 is substantially larger than the average RMS achieved by models 2 and 3 in both the training and testing data sets. To further understand the significance of the results from the neural network runs, the results were analyzed using single-factor Analysis of Variance (ANOVA). In this manner the significance of the hypothesized differences (one-sided tests) in the results from the models for different measures could be analyzed. As suspected, the results in Table III indicate that that there is a significant difference between models 2 and 1 and between models 3 and 1 for each of the four measures considered. In addition, the results confirm that no significant difference exists between the results for models 3 and 2. Model 2 actually had a higher mean value for the root mean squared error in the training data set and for the number of correct in the testing set in contrast to the hypothesized

Table III: ANOVA Results

	Comparison of Means					
	Model 2 - Model 1		Model 3 - Model 2		Model 3 - Model 1	
Measure	Difference	p-value	Difference	p-value	Difference	p-value
RMSE Training	- .153	.000	-.026	.999	-.155	.000
RMSE Testing	-.143	.000	.018	.943	-.125	.000
# Correct Training	54.167	.000	1.233	.999	55.40	.000
# Correct Testing	9.43	.000	-1.167	.892	8.267	.000

direction of the effect. Regardless, the overall results still indicate a high level of success in predicting intervention based on the patterns in conflict data with at least a 95% success rate in the testing data set for both models 2 and 3. For the sake of parsimony, additional use of the models and their results for decision making will be limited to the outputs from Model 2. It is possible that the inclusion of other variable combinations might produce results superior to those found in this study and model 2 is not believed to produce optimal results. However, it is believed that the pre-positioning inventory decisions can be assisted by the pattern recognition captured in the ouput probabilities of the model. A simplified example of how this may be accomplished will be the focus of the remaining portion of this paper.

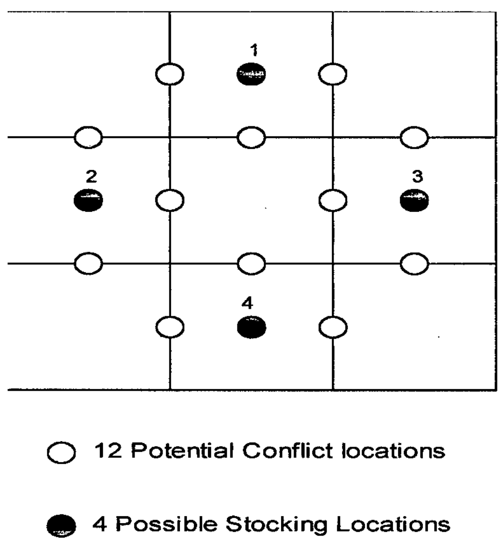
Logistics Decision Making Application

A well known and simple technique for determining where to build a facility is the load distance-method of comparison for different location options (Krajewski & Ritzman, 1996). This method simply selects the location with the minimum sum of all the load*distance values for all of the known demands in the region to be serviced by a facility. In planning for the construction of a new warehouse facility, such a technique may need to consider hundreds or even thousands of options before selecting the best

location. However for operations managers, the decision of where to preposition a predetermined quantity of materiel may be constrained to only a handful of currently constructed facilities.

For example, if a facility is to service an area containing nine adjacent countries and only four locations are available as the possible warehousing location then the problem may be represented as seen in Figure 2.

Figure 2. Euclidean Conflict and Stocking Location Map



For simplicity, we'll assume that the material can only be stocked at one location and that distances are measured using standard Euclidean distance calculations. For typical commercial enterprises a forecast of demand based on past and projected sales might be used to calculate the expected demand for each different locations in the service area. However, for prepositioned material, typically some amount of material equal to the average demand for an initial period (typically 15-45 days) is chosen as the stock level.

This stock allows time for a logistics pipeline to be developed and stock from outside the region to arrive if the demand does continue past thirty days or exceed anticipated levels. For this example, we'll assume that demand created by an individual conflict is a constant amount of five thousand units of material and that full replenishment occurs between each conflict occurrence. The location of these demands will be assumed to be at a point on the border of the countries involved in the conflict. Our analysis will first look at the decision of which location to select for stocking the 5000 units assuming that US will have an equal probability (1) of intervening in each of twelve possible conflicts identified in Figure 2. Then, this decision will be reevaluated by adjusting the original quantity demanded for each conflict based on the predicted intervention probability output from neural network Model 2 after randomly assigning

Table IV. Load-Distance Calculations for Conflict Response

	Country				
Conflict	A	B	Original Qty.	Model Probability	Expected Quantity
1	1	2	5000	0	0
2	1	4	5000	.314395	1571.975
3	2	3	5000	0	0
4	4	7	5000	.226611	1133.055
5	5	2	5000	.688458	3442.290
6	5	6	5000	0	0
7	5	4	5000	0	0
8	5	8	5000	.021436	107.180
9	6	3	5000	.621454	3107.270
10	6	9	5000	.073569	367.845
11	7	8	5000	0	0
12	8	9	5000	.855969	4279.845

Possible Location	Original Load-Distance Sum	Expected Load-Distance
1	304,015.9	74,569.53
2	304,015.9	80,802.71
3	304,015.9	64,270.24
4	304,015.9	69,882.53

values for the Region, Religion, Polity and Drug Involvement of the nine hypothetical countries being considered in Figure 2. For the analysis it is assumed that each potential conflict will occur only once and the results of the resulting load quantity calculations for the twelve conflicts are listed in Table IV. The results of this example show that without considering historical patterns in US intervention practices, no differentiation could be made between the locations based on the Original Load-Distance Sums for the four locations on the hypothetical Euclidean map. At this point, the decision of where to locate our prepositioned stock would have to rest on factors outside of the load-distance analysis. However, the use of the neural network provided intervention probabilities for the twelve conflicts that allowed the calculation of expected quantities which are quite different from the original quantity of 5000 units of demand for each conflict. This change in demand at the twelve conflict locations resulted in the calculation of four distinctly different Expected Load-Distance sums. These resulting sums allowed us to rank the performance of the four locations based on expected load-distance costs. From Table IV, Location 3 would be selected as the prepositioning stock location for our material based on its low score of 64270.24 with locations four, one and two following in rank order. In addition, an argument might be made that the five thousand units of material might be reduced to the average expected value from the analysis to protect solely against the long term expected quantities demanded from the stocking location. This question and others might be analyzed further in more advanced extensions of this example using simulation and heuristic search methods. These extensions will be discussed further in the Conclusion section. Regardless, this simple example seems to validate the claim that patterns in US intervention data can have a significant impact on

the decision of where to preposition inventory needed for future conflicts. In our example, a manager is able to progress from an inconclusive situation to a distinct differentiation between the four available location choices for stocking inventory.

CONCLUSION

The results of this analysis seem to provide a positive answer to the overall research question, "Can patterns in US military intervention be recognized using a small group of available variables" More specifically, the results of our analysis support our hypothesis that Model 2 would produce more favorable results than Model 1, however, our hypothesis that Model 3 would provide superior results to Model 2 could not be supported. The ability of both model 2 and model 3 to train and test successfully on 95% of the cases presented to the neural networks provided support that intervention patterns do exist. However, improvement in the models necessary to adequately model and predict 100% of intervention cases is an empirical question left to future research. The list of possible variables identified in Table I. provides at least a starting point for collecting data to improve on the three neural network models created in this study. However, finding a perfect model should not be considered the intent of this research. Instead, focus should remain on the improvement in decision-making that such pattern recognition can provide.

In our example, an improved load-distance method for applying neural network probabilities was applied to an inventory location problem. The results of this example, provided evidence that an inconclusive problem might be made clearer by applying neural network patterns to the decision making process. Further extensions of this

logistics analysis are possible through the relaxation of several of the assumptions in the example problem and by adding real world logistic constraints. First, different quantities demanded for the conflicts locations and the ability to simultaneously stock inventory at multiple locations will create the need to evaluate great numbers of feasible solutions instead of the four limited choices in this example. Simulation and sensitivity analysis of such a model might add further insight into the impact of US intervention patterns on inventory pre-positioning decisions. In addition, the use of heuristic search methods to find solutions to such a combinatorial optimization problem might be applied to evaluate which solution seems to provide the best solution to the inventory stocking location problem. Finally, future research might gain added realism by the use of actual geographic distance measures based on longitude and latitude or other known distance measures. One such measure which contains a circuitous routing factor to take into account the quality of roads in different countries or the use of different modes of transportation has been provided by (Bramel & Simchi-Levi, 1997).

Finally, the improvement of inventory positioning as addressed by this research has the potential to decrease costs and transportation times to move needed material and equipment to emergency locations in times of conflict. The decisions by managers of where to locate this material may actually be made months or even years in advance of the actual demand. However, making the best decision about prepositioning inventory can literally save lives and insure the success of military operations abroad. Finally, extension of this research to similar organizations that position inventory in anticipation of future unknown demands is believed to be possible. Humanitarian relief organizations and disaster relief agencies might find that patterns in historical demand might similarly

be recognized using neural networks in order to improve demand planning and improve positioning of inventory for their future operations.

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DEPARTMENT OF THE AIR FORCE
AIR FORCE INSTITUTE OF TECHNOLOGY

MEMORANDUM FOR AFIT PUBLIC AFFAIRS 18 December, 2001

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SUBJECT: Publication Clearance for Military Intervention Article

1. In order to expedite, the clearance process for the attached article, I am submitting the following additional information.

2. Although this paper may be used to aid the military positioning of inventory for war, it does not use military data on war reserve material, nor does it outline current policies or practices in this area of military operations. In addition, the paper uses solely historical data and does not indicate or suggest any biases by the US government toward any particular region or people of the world. It simply suggests that statistically significant historical patterns may be recognized using neural networks and used in future logistics planning by the military or other similar non-profit organizations.

3. In preparing the paper, I collected data from four separate locations. First, data on international disputes and conflicts was obtained on-line from Penn State University's Correlates of War public website. In addition, measures of democracy for the countries of the world was obtained on-line from the University of Maryland's Polity IV database. Information on the region, religion, economics and illicit drug trade for the countries of the world was obtained from the US Central Intelligence Agency's online public website called "Worldfactbook 2000." Finally, information on the oil reserves of the world was collected from the US Department of Energy's public website. Full reference citations to this informaton are included in the reference section of the paper.

4. Once approved, the article will be sent to the *Decision Sciences Journal*, an academic publication of the Decision Sciences Institute, for consideration for publication.

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